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Prediction of sludge volume index bulking using image analysis and neural network at a full-scale activated sludge plant

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ABSTRACT

Sludge volume index parameter should be monitored daily for the performance of wastewater treatment plants. It was aimed to estimate this parameter using image processing and artificial intelligence techniques for full-scale wastewater treatment plant. The activated sludge samples were collected from the aeration tank of the activated sludge process in Konya Domestic Wastewater Treatment Plant. Sludge characteristics and settling properties were observed microscopically via the measurements of flocs and filaments. The 49 images per slide were taken by an image-analysis system developed for automated image acquisition. A total of 120 samples were examined over a period of year. The floc and filament structures were analyzed using Cellular Neural Networks (CNN). Iteration value of the CNN was modified according to the image. Then, a number of morphological operations were applied for an accurate identification of the floc and filaments separately. Textural, shape, and statistical approaches were utilized for creating a set of data for each sample. After preparing the training and test data by shuffling the data randomly, a fivefold cross-validation method was applied. And, these training and test data were applied to an artificial neural network. The weights of the neural network were trained using the Levenberg–Marquardt, Genetic, and Artificial Bee Colony algorithms.

Keywords: Artificial bee colony algorithm; Artificial neural network; Genetic algorithm; Sludge bulking; Sludge volume index; Wastewater treatment

1. Introduction

Activated sludge flocculation is a very complex process that involves physical, chemical, and biological phenomena. The biological clarifier is one of the most important and critical steps of the activated sludge process. The main objectives of this are to provide good quality effluent and a well-settled and thickened activated sludge [1]. Sludge characterization is crucial

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for an efficient operation of the activated sludge process [2].

Image processing techniques are used for the segmentation of flocs and filaments, an estimation of biomass concentration [3,4], and an activated Sludge volume index (SVI) [5,6], as well as the prediction of bulking events [7]. A range of 30–200 images obtained from a slide were taken through systematic examination [5–8]. Morphological process at image analysis is generally used as a method for the segmentation of flocs and filaments. The image analysis method has been used to find the correlations between image analysis information ability and sludge settling using partial least squares [9]. A breakthrough about characterization and identification of the most common sludge abnormalities can be seen in several studies [2–10]. Image analysis is used for the examination of the size and shape of activated sludge flocs and to quantify them [11]. The published methods to predict the SVI leads to failure compared to other types of disturbances, since the biomass structure is different for each disturbance [12].

Nisar et al. reported that the structure and the amount of activated sludge flocs were helpful in the prediction of abnormal events in wastewater treatment plants. In their study, they segmented the images using edge detection technique. Later, they used morphological operations to identify relevant areas [13]. For differentiation of the flocs, Amaral, and Ferreirra have improved the image first by normalization and histogram equalization and then they softened the image by the wiener filter [14]. Kilander et al. performed a thresholding process using histogram data [15]. Heine et al. used the edge detection technique [16]. And, Perez et al. applied background removal, histogram equalization, median filtering, and morphological operations in their study [8].

Image analysis is used for monitoring of a wastewater treatment plant in order to eliminate the subjective, tedious, and rather tiring human analysis. In general, methods used for flocs and filament segmentation are the morphological processes, and the top-hat and bot-hat transforms. Both statistical and machine learning methods are used for defect analysis and estimation [9–12]. An efficient automatic microscopic image analysis with potential relevancy can be used as an early warning system for the excessive growth of the filamentous population in aeration tanks. Manual methods used for everyday operation of wastewater treatment plants are laborious and time consuming [17].

The SVI measures the settling characteristics of the sludge. Sludge bulking is a term to define the excessive growth of filamentous bacteria, this bulking is often also used for non-filamentous poor settling. As a general guideline, bulking is said to occur when the SVI is higher than 150 mL/g, regardless of its cause [17,18]. A low SVI generally indicates well-flocculated sludge with good settling properties. The SVI has been shown to be related to the floc structure in activated sludge [12]. The evolution of floc morphology was examined during variable-speed and constant-speed flocculation using image analysis [19]. In [20], flocculation is monitored by both microscopic image analysis and SVI. It is indicated that microscopic image analysis proves to be a powerful monitoring tool to evaluate the bioflocculation condition, while SVI is unable to correctly monitor its bioflocculation condition.

So far, most studies have used either the SVI or the diluted sludge volume index (DSVI, where all samples are diluted with deionized water to make them same in each analysis) measurements to describe the settleability of activated sludge. Some studies [2,7,9,10,13,21] have reported that in the case of filamentous or zoogleal bulking, the SVI or DSVI values were higher. However, unsatisfactory settling characteristics caused by either pinpoint floc formation or dispersed growth manifest themselves differently than do filamentous bulking or zoogleal bulking. In those cases, flocs can settle quickly, causing a lower or normal the SVI value, but small particles are not filtered out by the settling flocs and thus the actual purification result is poor [10,21].

Artificial neural network (ANN) techniques were utilized in various areas such as industry, safety, environment, medicine, along with image processing. These techniques are used for the suppression of noise [22–24], and especially for the estimation of the environmental data in treatment plants. Environmental data of the plants is used as input to estimate the output environmental data [25–27]. Reliable and systematic assessment methods are needed for controlling treatment plants. The data obtained on the treatment processes in the past were often modeled using artificial intelligence methods (neural networks, adaptive network-based fuzzy inference systems) and multiple statistical methods (principal component analysis and multiple linear regression).

Artificial Bee Colony (ABC) algorithm is used in various areas such as data mining applications, wireless sensor networks, image processing applications, and optimization problems [28,29] since it is efficient and stable in training ANNs [30]. The algorithm was proposed by Karaboga for optimizing numerical problems [31]. Karaboğa and Akay have used ABC for training ANN in signal processing applications, and compared the performance of the algorithm with differential evolution (DG) and particle swarm optimization (PSO) algorithms [32]. Karaboğa and Baştürk have also compared the performance of ABC with DG and PSO for multidimensional numerical problems [33]. Performance of ABC had also been compared with genetic algorithm (GA) and PSO [34]. Karaboğa et al. used ABC and ANN together to determine transfer function, architectural structure, and synaptic weights of each neuron [35]. ABC algorithms have been tested on benchmark classification problems, and the results have been compared with traditional neural network and population-based algorithms. In these comparisons, the ABC algorithm achieved good results [36].

It is seen in the recent literature that, image processing techniques are used increasingly in the estimation of SVI for full-scale wastewater treatment plant. In [17], a full-scale wastewater treatment plant was monitored over three months. Most flocculation studies have only been performed in the laboratory or on a pilot scale [7,12]. The results obtained in the experiments in laboratory scale will not give the same results for a full-scale plant. Thus, there is a need for full-scale studies. The evolution of floc morphology from poor flocculation to good flocculation in a full-scale wastewater treatment plant has not yet been studied [21]. The number of image analysis studies performed for biomass and sludge characterization in wastewater treatment is ever increasing, particularly in activated sludge systems. Determining the characteristics of microbial communities is still a challenge despite the various microscopy techniques applied. The sludge settling ability is considered as one of the main problems in activated sludge systems and is commonly measured by the SVI. The bulking conditions are identified with the SVI value. The sludge settleability strongly relates to the structure and properties of the activated sludge flocs. The aim of the proposed approach is to determine segmentation of floc images, having different characteristics, and to develop a model for predicting SVI concentrations and monitor the wastewater treatment plant performance. The SVI was estimated using the data-sets obtained through the image analysis performed by neural network for full-scale wastewater treatment plant.

2. Material and methods

Konya Wastewater Treatment Plant was designed to treat all domestic and pretreated industrial wastewater of the province of Konya, Turkey, based on a biological process. Activated sludge samples were taken from the aeration tank of the activated sludge process in the plant. The plant was observed on a regular basis. The aim of the proposed approach is to determine segmentation of floc images, having different characteristics, and to develop a model for predicting the SVI concentrations and monitor the wastewater treatment plant performance. The SVI was estimated using the data-sets obtained through the image analysis performed by neural network for full-scale wastewater treatment plant. The main steps of the system development are image acquisition, image analysis, segmentation, and prediction (Fig. 1).

2.1. Artificial neural network

ANNs are a technique for the human brain's problem-solving process. ANNs are a highly interconnected network of many simple processors. These simple processors, named artificial neurons, are organized into an input layer, a hidden layer (or layers) and an output layer. The neurons are connected by their weights. In this paper, the nodes of input layer and output layer are 33 and 1, respectively. Each neuron in the input layer represents a single input parameter. The number of hidden nodes is determined via experimentally. The neuron of the last layer represents the ANN output. The ANN can be evaluated as minimization of an error function in ANN training. Error function calculates the difference between the actual output of an ANN and a desired output. The mean squares of the errors are used as a performance function with its goal set to zero. The main steps are as following:

(1) Initialization: generate random weight and biases values in a specified range [−1, 1] and specified initial number of hidden layer sizes.

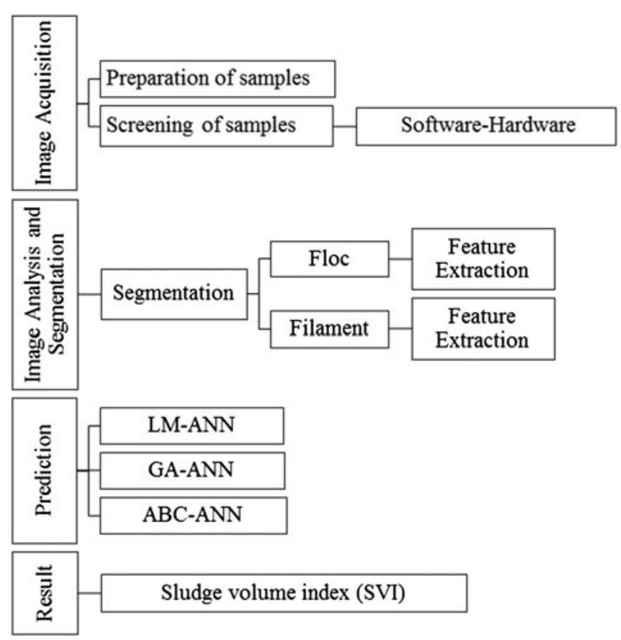

Fig. 1. Phases of the system development.

(2) Presentation of input and desired outputs: present the input vector $x(1)$, $x(2)$, ..., $x(N)$ and corresponding desired response $d(1)$, $d(2)$, ..., $d(N)$, N is the number of training sets.
(3) Calculation of actual outputs:

$$y_i = \varphi\left(\sum_{j=1}^{N_{M-1}} w_{ij}^{(M-1)} x_j^{(M-1)} + b_i^{(M-1)}\right), \quad i = 1, \ldots, N_{M-1} \tag{1}$$

where y_1, y_2, …, y_{NM} are the output signals.

(4) Adaptation of weights (w_{ij}) and biases (b_i):

$$\nabla w_{ij}^{(l-1)}(n) = \mu.x_j(n).\delta_i^{l-1}(n)$$

$$\nabla b_i^{(l-1)}(n) = \mu.\delta_i^{l-1}(n) \tag{2}$$

where

$$\delta_i^{(l-1)}(n) = \begin{cases} \varphi'(\text{net}_i^{(l-1)})[d_i - y_i], & l = M \\ \varphi'\left(\text{net}_i^{(l-1)}\right) \sum_{k-} w_{ki}\delta_k^{(l)}(n), & 1 \le l \le M \end{cases} \tag{3}$$

in which $x_j(n)$ = output of node j at iteration n, l is layer, k is the number of output nodes of neural network, M is output layer, and φ is activation function. The learning rate is represented by μ. After completing the training procedure, the weights of multilayer perceptron network are saved and ready for use. The results of the network are compared with the actual observation results and the network error is calculated. The training process continues until this error reaches an acceptable value [37].

2.2. Genetic algorithm

GA is a part of parallel search heuristics originated by the biological process of natural selection and evolution [38]. In GA optimization, solutions are coded into chromosomes in order to construct a population being evolved through generations. Each chromosome represents the weight vector of the network. At each generation, crossover operator is used, which is a process of taking more than one parent solutions and producing a child solution from them. Then, mutation and perturbation occurs for some of the individuals. After that, they are gathered to select new individuals for next generation. This procedure is repeated until the stopping criterion is satisfied [39].

2.3. ABC algorithm

ABC algorithm is an optimization algorithm based on a particular intelligent behavior of honey bee swarms. The algorithm represents solutions in the given multidimensional search space as food sources (nectar), and maintains a population of three types of bee (employed, onlooker, and scout) to search for the best food source. A bee waiting on the dance area for making decision to choose a food source is called onlooker and one going to the food source visited by it before is named employed bee. The other kind of bee is scout bee that carries out random search for discovering new sources [40].

2.4. SVI prediction

2.4.1. Image acquisition

The samples of activated sludge were collected from the aeration basins of the plant. Motic AE21 inverted microscope present in the laboratory was used for taking the images. The microscope was equipped with a visualization system that consists of a moticam microscope camera (Moticam 2500) and a motorized XY scanning stage (8MTF). An overview of the system equipment is shown in Fig. 2.

A properly prepared slide was placed on the microscope's stage for image acquisition. Each slide was scanned from top left corner to bottom right one systematically. The images were acquired at 1,288 × 966 pixels through an interface designed, at 40× magnifications.

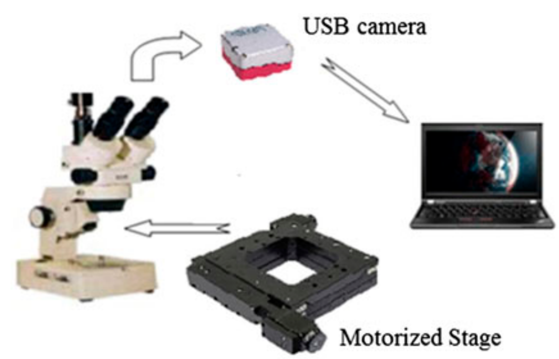

Fig. 2. An overview of the system hardware.

2.4.2. Image analysis and segmentation

The 49 (7 × 7) images per slide were taken by an image-analysis system developed for automated image acquisition in order to determine the floc size, shape, and structural parameters. As shown in Fig. 3, all the images were processed sequentially and the results obtained were recorded in Excel.

The methods generally used in the literature for the segmentation of flocs are basic image processing techniques such as thresholding, edge detection techniques, and morphological-based operations. In many studies, a preprocessing stage was applied, and then the objects were segmented using a predetermined threshold value.

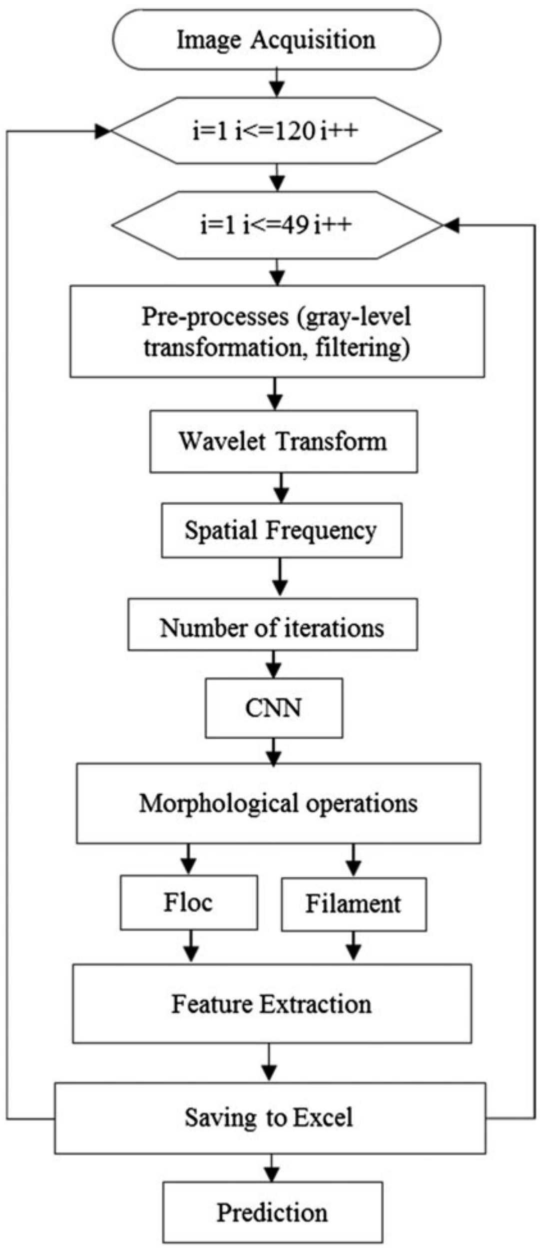

Fig. 3. Steps performed in processing the images.

Morphological characterization of flocs and filaments play a crucial role in evaluating the state of the activated sludge [11]. Therefore, segmentation stage is important and there are many studies in this regard. In this study, cellular neural networks (CNN) was utilized and the iteration value of the CNN was modified according to the image. Wavelet method was used to determine the Iteration value. Haar wavelet filter was used to perform second level of decomposition. The iteration value was calculated using the spatial frequency of subbands obtained as a result of this decomposition (the details of this value's calculation is available in [41]).

In determining the abnormalities in the activated sludge process, the filament and floc structures present in the images of the activated sludge images must be examined separately. The structures can be intertwined in the images. Morphological operations were applied after the CNN process in order to detect potential flocs and filaments as accurate as possible. There are free filaments and filaments combined with flocs in the images. The free filaments are the filaments or filaments portions outside the aggregates, either attached or dispersed in the bulk. Certain operations were applied to distinguish filaments combined with flocs, such as elimination of the small pixels, filling, opening, and dilating. Aggregates were pruned to eliminate filament branches connected to the flocs. Then the textural characteristics of each floc were determined. All the branches of the filaments inferior to very small areas were removed. In the segmentation of the filaments, the iteration value calculated in CNN was increased by 10% in order to identify small and indistinct ones. Then, morphological operations were applied.

2.4.3. Structure and training data

Experimental data required for this study has been collected from the activated sludge samples. Creation of the data-set through the images taken from a sample is shown in Fig. 4.

The total values, means, and standard deviations of the individual features derived from the images were calculated. The features shown in Table 1 were calculated. In addition to this table, a data-set was created using total filament length, total floc area, total area, features in the Table 1, and ratio of each parameters. Thus, 33 featured data-set were created for each sample.

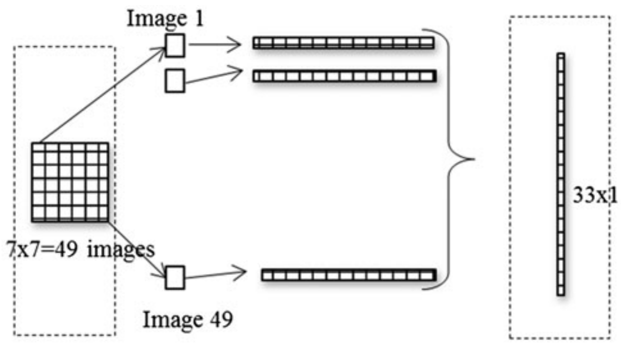

Fig. 4. The data obtained from a sample.

Table 1
The parameters calculated from the activated sludge images

Form factor	4 × pi × Area/Perimeter^2
Hole	Filed area/Area
Aspect ratio	AR = 1 + 4 × (length/width −1)/pi
Roundness	4 × Area/(pi × length^2)
Solidity	Area/Convex area
Extent	Area/Bounding area
Equivalent diameter	$\mathrm{De} = \sqrt{\frac{4}{\pi}\mathrm{Area}}$
Mean	$\sigma_g = \sqrt{\sum_{g=0}^{L-1}(g-\bar{g})^2 \mathrm{P}(g)}$
Standard deviation	$\bar{g} = \sum_{g=0}^{L-1} g\mathrm{P}(g) = \sum_r \sum_c \frac{I(r,c)}{M}$
Entropy	$\sum_{g=0}^{L-1} \mathrm{P}(g)\log_2[\mathrm{P}(g)]$
Contrast	$\sum_{n=0}^{N_g-1} n^2 \left\{ \sum_{i=1}^{N_g}\sum_{j=1}^{N_g} \mathrm{p}(i,j) \right\}, \quad \lvert i-j \rvert$
Correlation	$\frac{\sum_{i=0}^{N_g-1}\sum_{j=0}^{N_g-1}(i,j)-\mu_x\mu_y}{\sigma_x\sigma_y}$
Energy	$\sum_{i=1}^{N_g}\sum_{j=1}^{N_g} \mathrm{p}(i,j)^2$
Homogeneity	$\sum_{i=1}^{N_g}\sum_{j=1}^{N_g} \frac{1}{1+(i-j)^2}\mathrm{p}(i,j)$

The data-sets collected from the images were used to predict the SVI. In total, 33 input parameters were used. The data-set size was 33 segments × 120 samples. The ANN input parameters were converted into a vector that used the input of ANN. The vector was normalized between −1 and 1. This process was achieved by determining the maximum and minimum values of each variable over the whole data period and calculating normalized variables.

The performance of the proposed model was evaluated by calculating the mean square error (MSE) and the correlation coefficient between the modeled output and measurements of both the training and testing data-sets. MSE is the average of the squares of the difference between each output processing element and the desired output using the following formula:

$$\mathrm{MSE} = \sum_{i=1}^{N} \frac{(x_i - y_j)^2}{N} \tag{4}$$

where x_i and y_i are the measured and predicted values, respectively. N is the total number of model outputs.

The test results satisfying the minimum errors were subjected to testing of the correlation coefficient, r, as given in Eq. (3).

$$r = \frac{\sum(x-\bar{x})(y-\bar{y})}{\sqrt{\sum(x-\bar{x})^2 \sum(y-\bar{y})^2}} \tag{5}$$

where $\bar{x}$ and $\bar{y}$ are the average of the measured and predicted values, respectively. The range of r is from −1 to 1.

The network architecture chosen was 33:10:1. The number of hidden nodes was determined empirically. The ANN network model used is shown in Fig. 5.

The neurons are connected by their weights. We calculate the total weight as following:

$$\text{Total weight} = (\mathrm{NI}+1) \times \mathrm{NH} + (\mathrm{H}+1) \times \mathrm{NO} \tag{6}$$

where NI, NH, and NO are the number of input layer, hidden layer, and output layer processor, respectively [42].

For the 33:10:1 architecture, the total number of weights is calculated by Eq. (7). We calculate the total weight as 351. The weights of ANN were trained using Levenberg–Marquardt (LM-ANN), genetic (GA-ANN), and ABC-ANN algorithms. The same neural network architecture was used for all algorithms in order to see their relative strength.

GA and ABC algorithms are among the optimization techniques, which have been used in many studies to train ANN. It has been reported that ABC has provided improvements in multidimensional problems compared to the results obtained by PSO and GA [43].

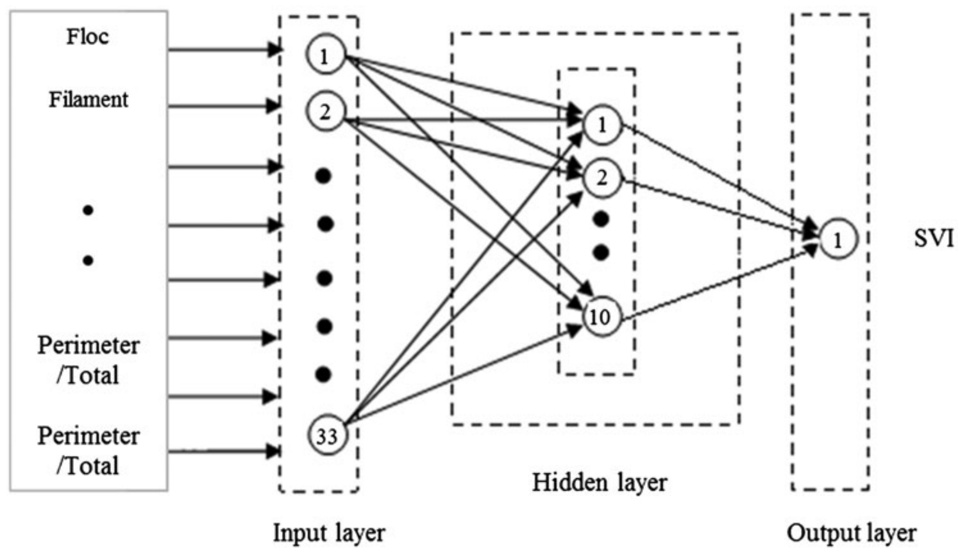

Fig. 5. The ANN model used to estimate the SVI.

Kurban and Beşdok have compared performances of GA, kalman filter algorithm and gradient descent algorithm in training radial neural networks and ANN by ABC, and found that ABC was more successful in ANN training [44]. They emphasized its superior performance in ANN training and lack of being stuck in local minima [45]. They have also stressed out that ABC has many superior aspects [46], leading to effective results [47]. And, they suggested use of ABC by revealing that it produces better results than conventional methods [48].

GAs are commonly used to optimize neural networks. Using GA in neural network training means that the weights of NN are determined by GA. Each chromosome represents the weight vector of the network. Here, the dimension of vector to be optimized was 351. In the numerical analysis, the GA control parameters were as follows: population size was $N = 20$; maximum generation number was 1,000; recombination probability was 0.1; crossover probability was 0.8; and, mutation probability was 0.02.

In the ABC algorithm, the bee was encoded to represent the network connection weights. Initially, the user defined size of employee bees was randomly initialized and initial weights were assigned. For each employee bee, the fitness was computed using MSE, which is the difference between the expected output and actual output of network. The probabilities of each of the employer bee were computed using fitness of the employer bee, which was used to initialize the onlooker bee. The fitness of each onlooker bee was computed. When the performance of bees didn't indicate an improvement for some user-specified time, then the scout bee was abandoned and replaced by the randomly initialized employee bee. This process was repeated for user-specified number of iterations. The best bee represents the final connection weights.

As for the modeling steps (training and testing) to be applied in ANN, K-fold cross-validation was used in our applications. The K-fold cross-validation is similar to random sub-sampling. Hence, K-fold partition of the data-set was created. For each of K experiments, K-1-folds were used for training and a different fold was used for testing. The advantage of K-fold cross-validation is that all the examples in the data-set are eventually used for both training and testing [49]. The data were divided into training and test subsets. Of these data, 80% was used for training, and 20% was used for the test set.

3. Results and discussion

The plant was followed for a year, and a total of 120 samples were examined. The SVI values were measured in the range of 70–211 ml/g in plant during this observation period. The sludge characteristics and settling properties were observed microscopically via the measurements of flocs and filaments. The designed interface was used at fixed intervals along the *xy*-axes to produce a single stack of 49 images for a given field of slide. Schematic diagram of the processes applied for the segmentation of flocs and filaments is shown in Fig. 6.

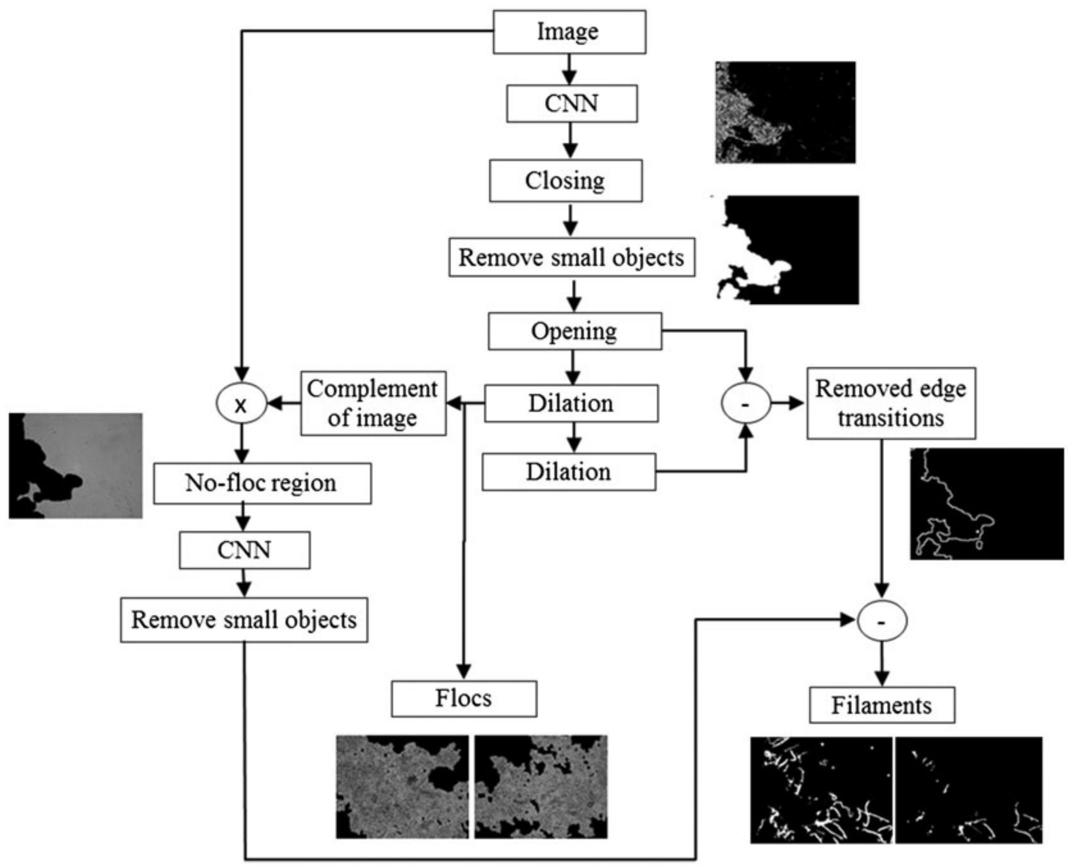

Fig. 6. The segmentation of flocs and filaments.

The structure of the flocs is of great importance in solid–liquid separation. Therefore, textural, shape, and statistical properties are utilized in determining the floc properties. The steps in Fig. 6 was taken for obtaining these properties. The edge transitions were ignored in order to obtain the textural properties of the flocs in a more accurate manner. These edge transitions were not included in neither floc nor filament properties.

The amount of free filaments in the sludge is important for the sludge properties. Therefore, the free filaments or the filaments touching flocs were separated from the image. Filamentous bulking events occur upon the excessive growth of filaments both inside and outside the flocs.

Sludge bulking is the most complex one among the settling problems occurring in the biological clarifiers. In general, the bulking is caused by excessive growth of filamentous bacteria. The term bulking sludge is also used for non-filamentous sludge with poor settling properties sometimes. It is important to know the relationship between floc size and its structural properties that affect SVI, since it can be used for process optimization.

Accordingly, the floc and filament structures were separated in the study. Both morphological and textural properties of the structures were estimated. The data-sets collected from the images were used for predicting the SVI. The data-set size was 33 segments × 120 samples. The neural network structure have one hidden layer. The hidden layer have 10 neurons. A tansig activation function was used in the

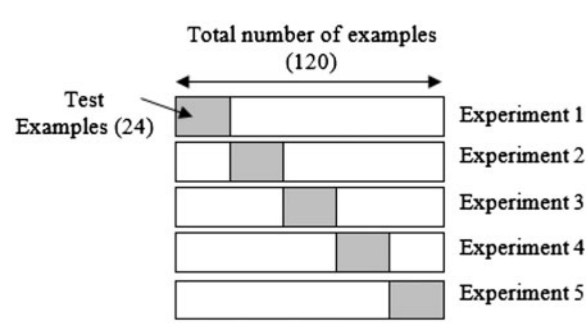

Fig. 7. Learning schemes for fivefold cross-validation methods.

Table 2
Comparison of learning algorithms

	Training		Testing	
Learning Algorithms	*r*	MSE	*r*	MSE
LM-ANN	0.997	0.00152	0.896	0.104
GA-ANN	0.973	0.04518	0.902	0.072
ABC-ANN	0.969	0.05292	0.915	0.094

hidden layer. A pure-linear activation function was used in the output layer. And, the number of weights to be trained was 351 in total. The weights of the neural network were trained by the LM, genetic and ABC algorithms using fivefold cross-validation.

The training and test data were obtained by randomly shuffling the data. And, these training and test data were applied to the ANN. Of the data, 1 in 5 was allocated for testing (24 data), and the remaining part (96 data) was used for training data. Fivefold cross-validation method was applied (Fig. 7). All these operations were repeated five times, and the accuracy results obtained in each run. Thus, an average accuracy was obtained. This procedure was performed for all learning algorithms made in the same way.

The performance of the methods was measured using correlation coefficient (r) and MSE function. The average MSE and r values obtained for training and test data-sets are shown in Table 2.

The best correlation value (0.915) between the estimation results and experimental the SVI parameter was found by the ABC-ANN method. The results showed that image processing and ANNs can be successfully applied for SVI estimation. The results indicated that the approach may have implementation potential for simulation, prediction, and bulking control of wastewater treatment plants. Automated image capturing and systematic scanning of samples are important processes for many applications. This would be helpful in everyday operation of a wastewater treatment plant substantially. The SVI was estimated using the data-sets obtained through the image analysis performed by neural network for full-scale wastewater treatment plant.

4. Conclusion

The estimation of the SVI value, which is an important parameter for the costly wastewater treatment plants, using image processing and artificial intelligence techniques will enable to monitor the problems related to rapid growth of filaments and lack of sedimentation in the sludge. The reason for the lack sedimentation cannot be determined by only using the SVI value. The filament and floc structures present in the images of the activated sludge images must be examined as necessary. By this method, the SVI value will be better evaluated thanks to the inclusion of textural, morphological, and statistical data of flocs and filaments. And, this will facilitate the operations of the workers, and will provide effective information regarding the negative effects and losses in the plants. The proposed system performs the long-lasting processes automatically, without requiring any user input. Conventional methods are rather time-consuming and costly, considering the repetition requirement of any erroneous experiment. Hence, the proposed method will minimize the need for experimental work.

In the activated sludge images, usually morphological and statistical properties were analyzed. In this study, textural properties of the flocs were also used.

ABC and GAs used for training ANN weights in many areas were also applied to the images taken from the wastewater treatment plant.

In subsequent studies, instead of images, videos can be captured in subsequent studies, and movements of protozoa and micro-organisms can be monitored in real time during this video capturing process.

In environmental engineering, the evaluation and modeling of the treatment processes by image processing methods of treatment processes will probably bring new horizons in the monitoring and control approaches. The results of such study will be beneficial both in producing economically feasible solutions and ease of operation in the operation of the wastewater treatment plants.

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